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Too Little Too Late

Welfare Impacts of Rainfall Shocks in Rural Indonesia

Emmanuel Skoufias
B. Essama-Nssah
Roy S. Katayama

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Abstract

The authors use regression analysis to assess the potential welfare impact of rainfall shocks in rural Indonesia. In particular, they consider two shocks: (i) a delay in the onset of monsoon and (ii) a significant shortfall in the amount of rain in the 90 day post-onset period. Focusing on households with family farm businesses, the analysis finds that a delay in the monsoon onset does not have a significant impact on the welfare of rice farmers. However, rice farm households located in areas exposed to low rainfall following the monsoon are negatively affected. Rice farm households appear to be able to protect their food expenditure in the face of weather shocks at the expense of lower nonfood expenditures per capita. The authors use propensity score matching to identify community programs that might moderate the welfare impact of this type of shock. Access to credit and public works projects in communities were among the programs with the strongest moderating effects. This is an important consideration for the design and implementation of adaptation strategies.

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Too Little Too Late: Welfare Impacts of Rainfall Shocks in Rural Indonesia

Emmanuel Skoufias
B. Essama-Nssah
Roy S. Katayama[1]

[1]Emmanuel Skoufias is a Lead Economist, Boniface Essama-Nssah is a Senior Economist, and Roy Shuji Katayama is an Economist, all at the Poverty Reduction and Equity Unit of the PREM Network at the World Bank, We wish to thank Will Martin, Syud Amer Ahmed, William Wallace, and two anonymous referees for useful comments in an earlier version of this paper.

1. Introduction

The adverse impacts of climate change[2] and extremes represent a serious challenge to development efforts around the globe and are likely to exacerbate the incidence, severity and persistence of poverty in many countries. The global mean surface temperature of the earth has been rising as a result of increased emission of greenhouse gases, particularly carbon dioxide (DFID 2004). Climate change and extremes are expected to affect mostly climate-sensitive sectors of the economy and in turn influence the pattern of household income and consumption. It is estimated that three-quarters of the world's poorest whose standard of living falls below $2 per day rely mostly on natural resources for their livelihoods (WRI 2008). The degradation of natural resources induced by climate change thus places significant stress on these livelihoods. As for agriculture, an important sector of activity for the poor, yields from rain-fed agriculture could be cut by half by 2020 in some parts of the world. It is feared that climate change could reduce soil fertility by 2 to 8 percent inducing a significant reduction in yields for a variety of crops.

However, very little is known about the welfare losses that households experience from these phenomena. Households at low levels of income are believed to be the most vulnerable to the impacts of climate change and extremes. This is due to their geographical locations, limited assets, limited access to resources and services, low human capital and high dependence upon natural resources for income and consumption. While there is wide recognition of this impending threat of climate change upon the poor, limited attention is given upon quantifying the poverty and distributional effects of climate change and identifying *adaptation* strategies and targeted measures that could mitigate the poverty impacts.

[2] According to the Intergovernmental Panel on Climate Change (IPCC) a narrow definition of climate refers to the statistical description in terms of the mean and variability of quantities such as temperature, precipitation and wind over a period of time ranging from months to thousands of years. The norm is 30 years as defined by the World Meteorological Organization (WMO). In a wider sense, climate refers to the *state* and the *statistical description* of a system composed of the following five components: atmosphere (gaseous envelope around the Earth), hydrosphere, cryosphere (snow and ice), land surface, and biosphere (all ecosystems and living organisms). For more details, please see Parry et al.(2007). Climate is different from weather which refers to atmospheric conditions in a given place at a specific time. The term "climate change" is used to indicate a significant variation (in a statistical sense) in either the mean state of the climate or in its variability for an extended period of time, usually decades or longer (Wilkinson 2006).

The purpose of this paper is to analyze the potential welfare impacts of rainfall shocks in rural Indonesia, and to draw relevant policy lessons. With an estimated population of 237.5 million, Indonesia is the largest archipelago and the fourth most populous nation in the world. Located in Southeastern Asia between the Indian and the Pacific Oceans, the country has a tropical climate with two distinct seasons, monsoon wet and dry, and is endowed with high levels of biodiversity. The country has been experiencing change in both mean *temperature* and *precipitation*. Since 1900, it is estimated that the annual mean temperature has increased about 0.3^{o} C. 1998 was the warmest year in the century as the temperature rose 1^{o} C above the 1961-1990 average (PEACE 2007). The increase in average temperature is projected to lie between 0.36 and 0.47^{o} C by the year 2020. It is reported that overall annual precipitation has decreased by 2 to 3 percent, but there are significant regional differences (WWF 2007). Southern regions such as Java, Lampung, South Sumatra, South Sulawesi, and Nusa Tenggara have seen *a decline in annual rainfall*. Northern regions on the other hand have experienced an increase in precipitation. These include most of Kalimantan and North Sulawesi. These changes in precipitation are strongly influenced by El Niño Southern Oscillation (ENSO). Indonesia tends to experience droughts during the warm phase of ENSO (i.e. El Niño) and excessive rain in the cool phase (i.e. La Niña). With the possible exception of southern Indonesia annual rainfall is expected to increase across the rest of the country (Naylor et al. 2002).

These observed and expected changes in climate are bound to have adverse impacts on the ecosystems, the associated resources and the lives of people who rely on these resources and on agricultural activities. *The 1997-1998 droughts associated with El Niño led to massive crop failures, water shortages and forest fires in parts of Indonesia, and likely exacerbated the impacts of the financial crisis at that time*. El Niño events tend to delay rainfall, leading to a decrease in rice planting in the main rice-growing regions in Indonesia such as Java and Bali. Adapting projections by the IPCC to local conditions, Naylor et al (2007) predict that by 2050 change in the mean climate will increase the probability of a 30-day delay in monsoon from 9-18 percent currently to 30-40 percent. This delay combined with increased temperature could reduce the yield of rice and soybean by as much as 10 percent. Our analysis considers the welfare implications of both a late monsoon onset and low level of rainfall. As we note later, a certain amount of rainfall is needed in the 90 day post-onset for rice to grow properly.

The paper is organized as follows. Section 2 presents the methodology focusing on the estimation of the impacts of rainfall variability on household expenditure per capita, our measure of welfare. The guiding view here is that the distribution of welfare losses associated with such events depends on the degree of household and community level *vulnerability* and *the moderating impact of existing assets and social protection institutions*. Understanding these factors plays an important role in designing policies to minimize exposure to and the impact of these shocks. Section 3 describes the available data while analytical results are presented in section 4. Concluding remarks are made in section 5.

2. Methodology

This section describes the methodology and analytical frameworks used in estimating the impacts of rainfall variability on household welfare in rural Indonesia and the potential moderating effects of community-based programs and infrastructure. We need to make our analytical framework consistent with the logic of vulnerability, the bedrock concept for the study of the welfare impacts of climate change and extremes. The distribution of economic welfare in any given society hinges crucially on individual *endowments* and *behavior* and the socio-political arrangements that govern *social interaction*. These factors (endowments, behavior and social interaction) also determine the distribution of vulnerability[3]. Adger (1999) emphasizes the connection between *individual* and *collective* vulnerability because it is impossible to consider individual achievement in isolation from the natural and social environment. Vulnerability of an individual or a household to livelihood stress depends crucially on both *exposure* and the *ability to cope* with and recover from the shock. Exposure is a function of, *inter alia*, climatic and topographical factors. The ability to cope is largely determined by access to resources, the diversity of income sources and social status within the community[4]. Increased exposure combined with a reduced capacity to cope with, recover from or adapt to any exogenous stress on livelihood leads to increased vulnerability.

[3] Vulnerability is usually taken as the likelihood that, at a given point in time, individual welfare will fall short of some socially acceptable benchmark (Hoddinott and Quisumbing 2008).

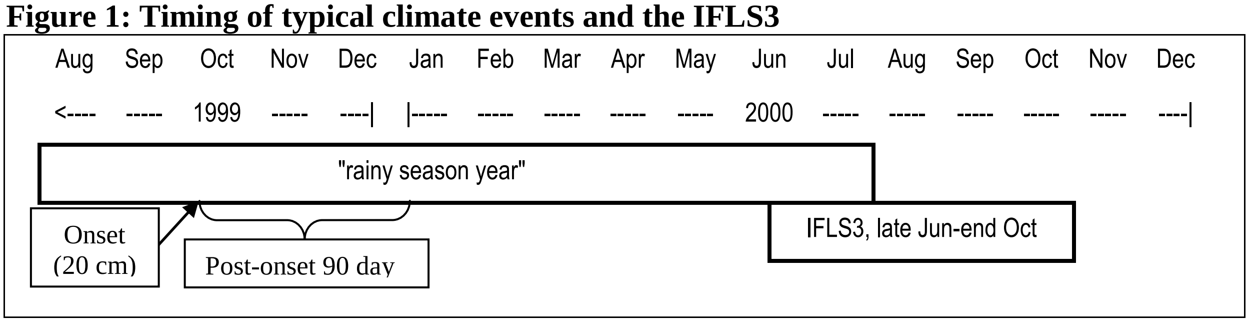
[4] Hoddinott and Quisumbing (2008) make essentially the same point by noting that, at the household level, vulnerability is determined by the nature of the shock, the availability of additional sources of income, the functioning of labor, credit and insurance markets, and the extent of public assistance.

Given the data limitations we face, we focus our strategy to exploiting cross-sectional variation in the data and linking some welfare indicator (e.g. consumption per capita) or some component thereof (food versus non-food expenditure) to a climate-related shock defined on the basis of available rainfall data focusing mainly on rural households. As noted earlier, the yield of crops such as rice (staple food in Indonesia) and soybean can is very much affected by changes in precipitation patterns which are strongly influenced by ENSO.

Given the importance of rice farming in the rural economy of Indonesia, we define climate shocks with reference to this activity. Naylor et al. (2007) explain that El Niño events can cause a delay in monsoon onset of up to 60 days. The same authors define "*onset*" as the number of days after August 1 when cumulative rainfall reaches 20 cm [5], and "delay" as the number of days above the mean onset date over the 1979-2004 period. Since farmers will typically begin planting after monsoon onset, late onset may affect prospects for a second harvest later in the season and possibly change crop combinations (with potentially significant consequences on production and market prices).

While delayed onset is an important determinant of harvest, we also need to consider the amount of rainfall after the onset. After farmers plant the rice fields, 60-120 cm of rainfall are needed during the 3-4 month grow-out period (Naylor et al. 2002). Thus, the second dimension of our shock involves the deviation of the amount of post-onset rainfall from the 25 year mean for each weather station. We define the amount of post-onset rainfall as the total amount of rainfall during the 90 day period following the monsoon onset date.

Figure 1: Timing of typical climate events and the IFLS3



The timing of these events in relation to the IFLS3 survey is illustrated in Figure 1. Considering that the degree of rainfall variability can differ across areas and that households may

[5] This is the amount of rainfall needed to moisten ground sufficiently for planting. It is believed that about 100 cm of rain are needed throughout the season for cultivation.

adjust farming practices accordingly, we use standard deviations from the inter-temporal mean to help account for such spatial differences. In terms of delay of monsoon onset, we define a negative shock as being more than one standard deviation *above* the 25 year mean. In terms of the amount of post-onset rainfall, we define a negative shock as being more than two standard deviations *below* the 25 year mean.

Given the interconnection between individual and collective vulnerability and adaptive capacity, our empirical analysis uses regressions to link an indicator of household welfare (real per capita total expenditure or its food and nonfood components) to some climate shock while controlling for household characteristics, and for the province of residence. We estimate a regression equation of the form,

$$y_{ij} = \beta_0 + \beta_1 X_i + \beta_2 S_j + \beta_3 (S_j * F_i)$$

where Y_{ij} represents per capita household expenditure of household *i* in community *j*, and X_i represents various control variables. S_j represents the covariate rainfall shocks, and F_i is a binary variable representing rice farming households.

After analyzing the effects of rainfall shocks on welfare, we consider the potential moderating effect of various community level programs. As Pitt et al. (1993) have argued, the placement of government programs is not likely to be random. One consequence of the endogeneity in program placement is that it is likely to result in biased estimates of program effects, especially when using cross-sectional data. Recognizing that government assistance programs are often targeted to poor areas, we use propensity score matching to investigate the difference that some community programs make with respect to mitigating the impact of the shock on household welfare. In particular, we restrict the sample to households exposed to the post-onset low rainfall shock. In line with treatment response literature, the treatment group consists of affected households residing in communities with a specific program or infrastructure (e.g. technical irrigation, safety net programs, access to credit, etc.) while the comparison group is made of affected households living in communities without such a program. Assuming that, conditional on observable community characteristics, program placement is as good as random we can consider two households with the same propensity score as observationally equivalent. Let one of these reside in a community with the program. The outcome of the other affected household residing in a community without the program represents a counterfactual outcome for the one in a community with the program. Here the propensity score is the probability of observing an affected household in a community with the program of interest as a function of some covariates. We estimate propensity scores on covariates using probit and retrieve their predicted values for matching "treated" observations with those in the comparison group. Specifically, for each program, a separate stepwise estimation of the probit specification was performed such that variables with a p-value less than 0.5 were added to the right hand side. The list of possible right hand side variables for the stepwise estimation included household and community variables. The household variables included: household size, age of head, marital status of head, gender of head, education level of head, household use of electricity, ownership of farmland, household nonfarm business, and household farm business. The community variables included: availability of public transport, availability of piped water, predominance of asphalt roads, share of households with electricity, distance to provincial capital, distance to district capital, and the shares of household heads with elementary, junior high, high school, and university level education.

We match each treatment household to its "nearest neighbor" based on propensity scores, restricting matches to the same year of the survey. We then compare average outcomes for affected households in the treatment group (i.e. in communities with a specific program or infrastructure) to the average outcome for similarly affected households in the comparison group (i.e. living in communities without the program under consideration).

To describe this somewhat more formally, let Y_i (1) denote the per capita expenditure outcome of household *i* in the presence of some "treatment" attribute in the local community, such as a safety net program or type of infrastructure, and Y_i (0) denote the per capita expenditure outcome of household *i* in the absence of the attribute in the local community. As both Y_i (1) and Y_i (0) are not observable, we use bias-corrected matching estimators, $\hat{Y}_i(0)$, in place of Y_i (0) (see Abadie and Imbens, 2002, and Abadie et al., 2004) and estimate the sample average treatment effect for the subpopulation of the treated (SATT):

$$SATT = \frac{1}{n_1} \sum_{i|W_i=1} \left\{ Y_i(1) - \hat{Y}_i(0) \right\},$$

where $W_i=1$ indicates that a household is in a community with the treatment attribute, and n_1 is the sample size of the treated.

3. Data

We are able to study the impacts of extreme weather events on rural households by merging household and community level data from the Indonesian Family Life Survey (IFLS) with daily rainfall data covering a 25 year period. The combined data set contains information on rainfall, household expenditures, household level socio-economic characteristics, and community level attributes.

Household and community surveys were fielded from late June to the end of October 2000 for IFLS3 and from August 1997 to January 1998 for IFLS2. The surveys include village-level data which allows the determination of the extent to which access to better infrastructure or social programs increases resiliency. The consumption aggregate consists of food and nonfood components. The food component consists of 37 food items (purchases and the value of own production or gifts) consumed within the last week. The nonfood component consists of frequently purchased goods and services (utilities, personal toiletries, household items, domestic services, recreation and entertainment, transport, sweepstakes), less frequent purchases and durables (clothing, furniture, medical, ceremonies, tax), housing, and educational expenditures for children living in the household. Transfers out of the household were excluded. All values are monthly figures and are in real terms. To obtain real values, both temporal and spatial deflators were used, using prices in December 2000 in Jakarta as the base.[6]

Using daily rainfall data from 1979 to 2004, we calculated the 25 year mean and standard deviations for monsoon onset and the amount of post-onset rainfall for 32 weather stations. The rainfall data from these weather stations were then matched to communities in IFLS. Weather data were merged with household survey data at the community level based on proximity. Only weather stations with complete data for the 25 year period were used. The matched data contained a total of 267 communities and 32 WMO stations. In rural areas, 106 communities in 9 provinces were matched to 27 stations. In rural Java, 66 communities in 4 provinces were matched to 18 stations. The number of communities per WMO station ranged from 1 to 10 in rural areas. 3,290 households were matched to 27 stations in rural areas, and 2,159 households were matched to 18 stations in rural Java.

[6] The spatial deflator used is the ratio of the location (province, urban/rural area) poverty line (in December 2000 prices) to the Jakarta poverty line. Thus the spatial deflator used converts the local December 2000 values into Jakarta December 2000 values.

After merging available precipitation data and dropping observations with missing data, the sample size in the 2000 IFLS3 for our analysis was reduced to 6,188 households from a total of 10,292. In our 2000 sample, 3,290 households were located in rural areas, and of these 2,159 were located on Java. Data from additional weather stations would benefit this analysis by improving the level of disaggregation of weather data, but these data could not be obtained.

Figure 2: Variation in monsoon onset and post-onset rainfall

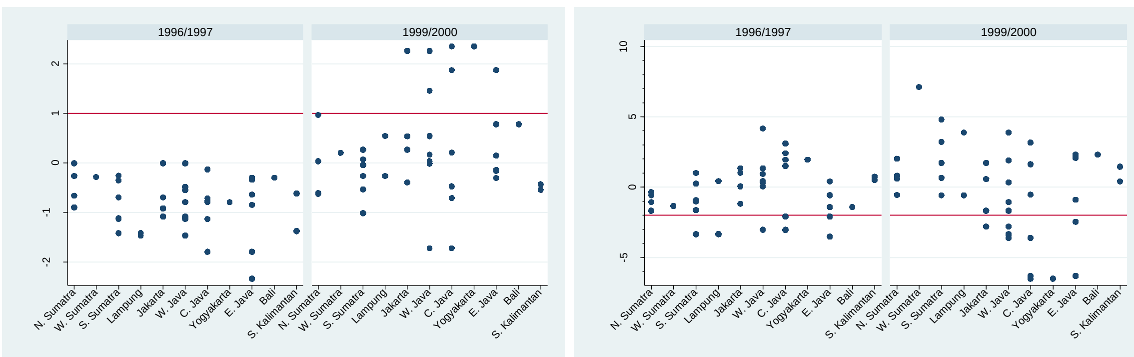


Figure 2 shows variation by province in monsoon onset and post-onset rainfall. With respect to delays in monsoon onset, only provinces in Java experienced a delay greater than one standard deviation from the 25 year mean in 1999/2000. As for the amount of rainfall during the 90 day post-onset period, the data indicate that only provinces in Java experienced rainfall below two standard deviations from the 25 year mean in 1999/2000.

The summary statistics of household expenditures, household characteristics, and rainfall shock exposure in rural Java are shown in Table 1. The majority of household heads were married males who did not have more than an elementary education. The vast majority of households utilized electricity. Half of the households owned farmland, and 44% were engaged in non-farm businesses. Nearly 60% of households were engaged in a farm business, 38% with rice as the most valuable crop and 22% with another crop as the most valuable. 34% of households in our sample were exposed to the delay of onset shock and 45% were exposed to the post-onset low rainfall shock. The correlation coefficient between these two shock variables for our sample was not large at 0.38.

Table 1: Summary Statistics for Households in Rural Java (1999/2000 IFLS)

Variables	Mean	Std. Err.
total pce (Rupiah per capita per month)	257273	7660
food pce (Rupiah per capita per month)	154389	4332
nonfood pce (Rupiah per capita per month)	102885	4745
household size	3.06	0.09
age of head	48.41	0.45
married head	0.84	0.01
female head	0.18	0.01
highest education of head: elementary	0.58	0.02
highest education of head: jr. high school	0.07	0.01
highest education of head: high school	0.05	0.01
highest education of head: university	0.08	0.01
hh utilizes electricity	0.90	0.03
hh owns farmland	0.50	0.03
hh non-farm business	0.44	0.03
hh farm business - rice most valuable crop	0.38	0.03
hh farm business - other crop most valuable	0.22	0.03
shock: delay of monsoon onset (>1 sd)	0.34	0.06
shock: delay of monsoon onset (>2 sd)	0.16	0.04
shock: post-onset low rainfall (<-1 sd)	0.57	0.06
shock: post-onset low rainfall (<-2 sd)	0.45	0.06
N=2159		

4. Empirical Results

We present our findings on (i) the impact of rainfall shocks on per capita household consumption levels and (ii) the role that various social programs may have played in mitigating the negative welfare impacts of the rainfall shocks. For the first part, we used regression analysis to quantify the average reduction in household welfare levels for those exposed to low rainfall shocks. For the second part, we used propensity score matching to estimate the extent of moderating effects offered by the various community-based programs.

Welfare Impacts of Rainfall Shocks

Given the importance of rain-fed agriculture, in particular rice farming, to rural livelihoods in Indonesia, we study the potential impact of rainfall shocks on per capita total household expenditure, and its food and nonfood components. We focus on rural Java, the predominant rice production area in Indonesia, and use regression analysis to estimate the impacts on household expenditures.

We include in our regressions two binary variables representing the two rainfall shocks defined earlier, delayed monsoon onset and post-onset low rainfall. We interact these shock variables with a binary variable for rice farming households, specifically households engaged in a farm business with rice as the most valuable crop. This is done to differentiate the effect of the shocks between households that have and do not have a farm business with rice as the most valuable crop. In the regressions, we control for various household characteristics: household size, age of household head, sex and marital status of head, level of education of the head (binary variables for elementary, junior high, high school, and university), access to electricity, ownership of farm land, and household farm and nonfarm business activity, whether or not rice is the most valuable crop, and province of residence. The reference case is a household in rural West Java province, with an uneducated, single, male head, that has no access to electricity, no farm land, and no household farm or nonfarm businesses.

Using the two rainfall shock variables separately as well as together, we used three different specifications for our regressions. The first includes a binary variable for delayed monsoon onset along with its interaction term with the binary variable for rice farming household. The second substitutes the post-onset low rainfall variable as the shock variable. The third includes both rainfall shocks along their interaction terms. This third variation was used with different dependent variables, that is, per capital total household expenditure and its food and nonfood components.

As might have been expected, there is a strong positive correlation between household per capita expenditure and assets: education and ownership of farmland. All education coefficients are positive and significantly different from zero. For all five of the regressions reported in Table 2, the magnitude of these coefficients increase with the level of education up to high school, but the coefficients for university education are less than those associated with high school, which is a rather unusual. In general, the province of residence does not seem to matter in the explanation of variations in household welfare as the associated coefficients are not significantly different from zero. Having electricity is certainly an indication of wealth. This is manifested by a positive and significant effect on per capita expenditure. Similarly, owning farmland or a non-farm business has a positive and significant impact on household expenditure and its components (food and nonfood).

In the absence of a weather shock, our results show that there is no statistically significant difference between the average welfare of households for which rice is the most valuable crop and that of the reference household (Table 2). On the other hand, we find that households running a farm business with non-rice crops as the most valuable had per capita nonfood expenditures about 12 percent lower than the reference household.

The definition of the rainfall shock variable is important in our specifications. While a shock defined by the delay in the monsoon onset has a negative effect on the per capita total expenditures of rural households of Java, it is not statistically significant. This is contrary to that reported in Korkeala et al. (2009) based on panel data. However, when we look at the food component of expenditures, a delay of monsoon onset shock is associated with a 13 percent drop in per capita food expenditures relative to the reference household.

If the amount of rainfall during the 90 day post-onset period is below 2 standard deviations away from the 25 year mean, the coefficients associated with the interaction between the post-onset low rainfall shock and rice farming are negative and significantly different from zero (at a 5 percent level of significance) for total and nonfood expenditures. With exposure to the low rainfall shock, the per capita total expenditure of households engaged in rice farming is 12 to 14 percent lower than that of the reference household and the per capita nonfood expenditure is 26 percent lower, controlling for household attributes and province of residence. In constrast we find that the interaction of the low rainfall shock with the binary variable identifying households engaged in rice farming does not have a statistically significant effect on food consumption. This result, which is frequently observed among rural households in different countries (Skoufias, and Quisumbing, 2005), suggests that rice farm households are able to protect their food consumption in the face of weather shocks. Thus, households manage to protect their food consumption at the expense of nonfood consumption. To the extent that reduced expenditures on nonfood are accompanied by lower expenditures on children’s education, weather-related shocks may also be associated with reduced investment in the human capital of children (Jacoby and Skoufias, 1997).

Table 2: Regression Results of Shocks on Household Consumption in Rural Java, 1999/2000

Dependent Variable (log):	total pce						nonfood pce		food pce	
	delay of onset shock (1)		post-onset low rainfall shock (2)		both shocks (3)		both shocks (4)		both shocks (5)	
household size	-0.145	***	-0.145	***	-0.145	***	-0.136	***	-0.148	***
	(0.008)		(0.009)		(0.008)		(0.011)		(0.008)	
age of head	0.015	**	0.015	**	0.015	**	0.017	**	0.016	***
	(0.006)		(0.006)		(0.006)		(0.008)		(0.006)	
age of head^2 (1/100)	-0.015	***	-0.015	***	-0.015	***	-0.019	**	-0.015	***
	(0.005)		(0.005)		(0.005)		(0.007)		(0.005)	
married head	0.036		0.042		0.041		0.016		0.102	
	(0.077)		(0.076)		(0.077)		(0.086)		(0.078)	
female head	-0.019		-0.015		-0.016		0.007		0.012	
	(0.077)		(0.076)		(0.076)		(0.079)		(0.079)	
highest education of head: elementary	0.091	**	0.086	**	0.087	**	0.172	***	0.039	
	(0.044)		(0.042)		(0.042)		(0.051)		(0.045)	
highest education of head: jr. high school	0.214	***	0.206	***	0.207	***	0.358	***	0.123	
	(0.071)		(0.070)		(0.070)		(0.085)		(0.075)	
highest education of head: high school	0.506	***	0.502	***	0.503	***	0.786	***	0.300	***
	(0.084)		(0.083)		(0.083)		(0.093)		(0.087)	
highest education of head: university	0.212	**	0.205	**	0.205	**	0.350	***	0.098	
	(0.099)		(0.095)		(0.095)		(0.117)		(0.088)	
Central Java province (33)	-0.072		-0.055		-0.057		-0.007		-0.075	
	(0.076)		(0.073)		(0.073)		(0.097)		(0.068)	
Yogyakarta province (34)	-0.038		0.004		0.005		0.044		-0.023	
	(0.114)		(0.106)		(0.112)		(0.134)		(0.115)	
East Java province (35)	-0.071		-0.063		-0.061		-0.016		-0.106	**
	(0.058)		(0.057)		(0.056)		(0.088)		(0.047)	
hh utilizes electricity	0.158	**	0.188	***	0.188	***	0.441	***	0.060	
	(0.066)		(0.062)		(0.062)		(0.106)		(0.063)	
hh owns farmland	0.114	***	0.117	***	0.116	***	0.131	***	0.080	**
	(0.032)		(0.032)		(0.032)		(0.046)		(0.033)	
hh non-farm business	0.172	***	0.170	***	0.170	***	0.228	***	0.131	***
	(0.035)		(0.034)		(0.034)		(0.044)		(0.034)	
hh farm business - rice most valuable crop	0.002		0.056		0.041		0.072		0.034	
	(0.042)		(0.047)		(0.046)		(0.065)		(0.042)	
hh farm business - other crop most valuable	-0.046		-0.047		-0.046		-0.117	**	0.003	
	(0.044)		(0.046)		(0.045)		(0.054)		(0.048)	
shock: delay of monsoon onset (>1sd)	-0.042				-0.035		0.103		-0.132	**
	(0.064)				(0.065)		(0.084)		(0.061)	
shock: post-onset low rainfall (<-2sd)			-0.036		-0.027		-0.034		-0.019	
			(0.054)		(0.055)		(0.076)		(0.049)	
hh farm rice X delay shock	0.024				0.072		0.037		0.118	*
	(0.062)				(0.072)		(0.114)		(0.063)	
hh farm rice X low rainfall shock			-0.120	**	-0.142	**	-0.256	**	-0.083	
			(0.059)		(0.067)		(0.104)		(0.057)	
constant	11.972	***	11.946	***	11.952	***	10.431	***	11.574	***
	(0.199)		(0.193)		(0.191)		(0.277)		(0.170)	
N	2159		2159		2159		2159		2159	
r2	0.196		0.2		0.201		0.189		0.175	
legend: p<0.10 *, p<0.05 **, p<0.01 *** ; standard errors in parentheses above										

Role of Community Programs

As noted earlier, vulnerability of an individual or a household to livelihood stress depends on both exposure and the ability to cope with and recover from the shock. The ability to cope is largely determined by access to resources including community-level infrastructure and assistance programs. We explored the role of the following seven community level resources or programs in mitigating negative welfare impacts of shocks in rural areas of Java: (1) presence of technical irrigation in the community[7], (2) Kampung Improvement Program (an informal housing area upgrading program that provided basic services and infrastructure through community based organizations), (3) Infrastructure Development Program (a community-based infrastructure development program), and (4) availability of credit through the INPRES Poor Villages Program, (5) the village has a *Padat Karya* program, a loose collection of labor-intensive programs sponsored by various government departments (Sumarto et al. 2002), (6) the village had a PDM-DKE (Regional Empowerment to Overcome the Impact of Economic Crisis) program, a block grant program for villages to support public works or revolving funds for credit (Sumarto et al. 2002), and (7) the *Inpres Desa Tertinggal* (IDT) (Program for Underdeveloped Villages), another block grant program targeting extremely poor villages (Sumarto et al. 2002). Data on the first four community level programs above were available in both the 1997 and 2000 IFLS surveys, so we pooled the data to increase the number of observations. However, data on the last three community-based programs above were only available in the 2000 IFLS survey, so we could only use the single year of observations in evaluating those programs.

As discussed earlier, recognizing that government assistance programs are often targeted to poor areas, we use propensity score matching to infer the moderating impact of some community level interventions on the impact of the shock. For each of the community-based programs, we estimate the average treatment effect of the intervention on per capita household expenditures components (total, nonfood, and food) among households exposed to the shock and located in communities with the program of interest (i.e. SATT, or the sample average treatment effect for the treated). The results in Table 3 are shown as the percent difference in mean per capita expenditures between the treatment and comparison groups. The panel on the left side of Table 3 relates to the sample of households of rural Java that were exposed to the post-onset low rainfall shock regardless of occupational status, while the panel on the right focuses on the sub-sample of households exposed to the shock that were engaged in a farm business.[8]

[7]Data only indicated whether technical irrigation existed in the community, not household use of technical irrigation.

[8] We also attempted to extend this analysis to only farmers indicating rice as the most valuable crop, but the data thinned out and precluded application of this approach to this sub-sample.

Table 3: Moderating Effects of Community-Based Programs for Households in Rural Java Exposed to Post-Onset Low Rainfall Shocks: Average Treatment Effects based on Propensity Score Matching

	Average Treatment Effect of Community-Based Programs (percent difference between treatment and comparison groups)					
Sub-sample:	All households exposed to low rainfall shock			Households engaged in farm business and exposed to low rainfall shock		
Components of per capita expenditure:	Total	Nonfood	Food	Total	Nonfood	Food
Technical Irrigation ‡	12.6 **	27.0 *** n=884	3.1	24.3 ***	46.7 *** n=575	8.9
Kampung Improvement Program ‡ (community-based)	8.0 *	20.7 *** n=1107	-0.9	6.9	17.4 ** n=838	-3.0
Infrastructure Development Program ‡ (community-based)	13.9 **	10.3 n=632	18.5 ***	-5.0	-9.9 n=509	-2.5
INPRES Poor Villages Program ‡ (credit)	25.0 ***	4.6 n=1390	38.2 ***	11.0	-12.8 n=959	28.8 ***
Padat Karya Program † (public works)	16.3 ***	23.5 *** n=1033	13.8 **	2.7	15.7 n=632	-4.0
PDM-DKE Program † (block grants)	18.9 ***	23.9 *** n=544	18.6 **	9.5	21.5 n=216	9.1
Either of the two programs above †	28.3 ***	31.4 *** n=722	30.0 ***	14.7 *	20.5 * n=514	14.5 *
IDT Program † (block grants)	17.7 ***	14.5 * n=978	18.2 ***	33.4 ***	39.2 *** n=352	35.9 ***

legend: $p < 0.1$ *, $p < 0.05$ **, $p < 0.01$ ***
‡ Pooled data from 1997 IFLS2 and 2000 IFLS3 ; † Data from 2000 IFLS3 data only

Focusing on the sample of households of rural Java, we find that households exposed to the rainfall shock but residing in communities with the infrastructure or programs mentioned above have on average a significantly higher level of per capita expenditure than households in the comparison group. Households in communities with the INPRES credit program had an average of 25% higher total per capita expenditure and 38% higher food per capita expenditure than comparison households, suggesting that the program furnished an important coping mechanism to households affected by the shocks. The Padat Karya (public works) and PDM-DKE (public works / credit) safety net programs also appear to have helped households cope with the impacts of the shocks. The difference in average total per capita expenditure between households with and without Padat Karya in their community was 16.3%, and for PDM-DKE, the difference was 18.9%. The differences in the food component of per capita expenditure were 13.8% and 18.6% for Padat Karya and PDM-DKE respectively, while the differences in the nonfood component were about 24% for both programs. If either of these safety net programs are available in the community, the average treatment effect is 28.3% for total per capital expenditure, 31.4% for the nonfood component, and 30% for the food component. The average treatment effects for the IDT program were 18% for both total and food per capita expenditure.

The presence of technical irrigation in the community appears to have helped mitigate the impact of the shocks, as the difference in average per capita expenditure between treatment and comparison groups were 12.6% and 27% for total and nonfood per capita expenditure respectively. The community-based programs to improve local infrastructure also appear to have helped households. The average treatment effect for the Infrastructure Development Program was 13.9% for total per capita expenditure (18.5% for food component) and for the Kampung Improvement Program, about 27% for nonfood per capita expenditure and no significant difference for total and food per capita expenditure.

As for the subsample of households engaged in farm businesses in rural Java, the right side of Table 3 reveals a few community characteristics with statistically significant results in moderating the impacts of the shocks. First, technical irrigation in the community amounted to an average 24.3% higher total per capita expenditure (and 46.7% higher nonfood per capita expenditure) among farm households than the comparison group. Second, the Kampung program facilitated higher nonfood per capita expenditure (17.4%) but no significant differences for total and food per capita expenditure. Third, farm households with the INPRES program in their community had 28.8% higher average food per capita expenditure relative to the comparison group, again suggesting its positive role in assisting households cope with shocks. Fourth, the existence of the IDT program in a community was found to have a significant positive effect in moderating the impact of the shock for farm households, that is, 33.4%, 39.2%, and 35.9% higher total, nonfood, and food per capita expenditure respectively, relative to the comparison group.

The results above suggest that access to credit and public works projects in communities can help households cope with shocks and thereby play a strong protective role during times of crisis. On the other hand, technical irrigation and infrastructure improvement programs in communities are likely to help mitigate the impacts of the shocks. In light of these findings, these policy instruments should be given due consideration in the design and implementation of adaptation strategies.

5. Concluding Remarks

Very little empirical evidence exists on the welfare losses that households experience as a consequence of weather shocks. In principle, households at low levels of income are most vulnerable to the impacts of weather extremes given their geographical locations, limited assets and access to resources and services, low human capital and high dependence upon natural resources for income and consumption. While there is wide recognition of the impending threat of climate change upon the poor, limited attention is given to quantifying such effects of climate change and identifying household *adaptation* strategies and targeted measures that could mitigate the poverty impacts. This paper seeks to make a contribution by analyzing the potential welfare impacts of rainfall shocks in rural Indonesia with a focus on households engaged in family farm businesses, in particular rice farming. It also attempts to identify community characteristics capable of dampening the adverse impact of climate change and extremes. The focus on rice farming is due to the fact that rice is a staple food in Indonesia.

The basic approach adopted here is to exploit cross-sectional variation in the data and link a welfare indicator (i.e. real consumption per capita) or some component thereof (i.e. food versus non-food expenditure) to a weather shock defined on the basis of available rainfall data focusing mainly on rural households. In particular, we consider two types of shocks: delayed onset of monsoon and rain shortfall in the 90 day period following monsoon onset. We find that delay in the monsoon onset does not have a significant impact on the welfare of rural households. However, rice farm households located in areas experiencing low rainfall following the monsoon onset are negatively affected by the low rainfall shock. Nonfood expenditure per capita is the most affected component. This suggests that rice farm households protect their food expenditure in the face of weather shocks. Further study is needed to better understand these choices and their implications for adaptation strategies.

We use propensity score matching to identify potential policy instruments that might moderate the welfare impact of climate change and extremes. Our results indicate that credit availability, the existence of safety nets and community-based programs offer the strongest cushion for these types of shocks. This is an important consideration for the design and implementation of adaptation strategies. Indeed, individual ability to cope with and recover from crises hinges critically on available social support. Taken together with other emerging evidence on the long lasting effects of rainfall shocks on human capital, our findings highlight the urgent need for effective adaptation strategies.

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